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Precision livestock farming for pigs

Erik Vranken†‡ and Dries Berckmans§

† M3-BIORES– Measure, Model & Manage Bioresponses, KU Leuven, Kasteelpark Arenberg 30, B-3001 Leuven, Belgium

‡ FANCOM B.V., Research Department, P.O. Box 7131, 5980 AC Panningen, The Netherlands

§ SoundTalks, Kapeldreef 60, 3001 Leuven, Belgium

Implications

It was demonstrated that laboratory-developed precision livestock farming (**PLF**) tools can be fully operational on farms and can bring value to the farmers and other stakeholders in the production chains. In the PLF concept, the animal is used as a sensor, and algorithms translate the measured animal responses into key indicators for optimal performance, improved animal welfare, and farm sustainability. In a further development phase, PLF applications assist farmers in taking their daily management decisions and generate early warnings when something is going wrong in the production process. Attention must be paid to adequate training of farmers and the further integration of PLF system in operational management systems.

Introduction

To guarantee accurate and continuous monitoring of individual animals at a modern livestock farm, farmers nowadays need reliable and affordable technologies to assist them in performing daily management of tasks. The application of the principles and techniques of process engineering to livestock farming to monitor, model, and manage animal production is called precision livestock farming (**PLF**). Precision livestock farming seems like the only realistic way to support farmers and other stakeholders in the livestock production chain in the near future while at the same time coping with the rising demand for meat.

Precision livestock farming is a series of practices aimed at increasing the farmer's ability to keep contact with individual animals despite the growing intensification of livestock production. It aims to achieve economically, environmentally, and socially sustainable farming through the observation, behavioral interpretation, and control of the smallest possible group of animals. It enables farmers to reduce operational costs such as expenditures to feed, medication, and energy. Moreover, farmers can use PLF technologies to monitor animal health and welfare to ensure that animals live well and are free of diseases. Precision livestock farming systems aim to translate the output of the technology to useful information to the farmer.

Commercial products need a combination of hardware complying with certain technical and safety standards in combination with software, a good user interface, a backup solution to store data, an auto-restart function in case of power failure, manual and help functions, and installers who can install and service the product, etc.

Results and potential of PLF technology are mostly unknown to animal scientists, veterinarians, ethologists, etc. due to a lack of collaboration among different disciplines. However, there is no doubt that the combination of new technologies with biology offers great opportunities for the EU in terms of realizing and implementing directives as well as in economic and social terms.

A lot of data are already automatically registered by the in-house control computers and collected on a farm computer. In practice, however, the pig farmers hardly use this information. As a result, they miss out on money because deviations in the production process are not noticed or noticed too late. However, the biggest challenge with PLF is to convert this growing amount of data into usable information so that, throughout the day, the farmer can use the relevant information directly to manage operations.

Examples of Precision Livestock Farming Systems for Pigs

In the PLF approach, the traditional environmental measures (temperature, humidity, and CO_2) are extended with direct measures of animal responses by means of feed intake sensors, growth monitors, cameras, and microphones. In this concept, the animal is used as a sensor, and algorithms translate the measured animal responses into key indicators for optimal performance, improved animal welfare, and farm sustainability. In a further development phase, PLF applications will assist the farmer in taking his daily management decisions and generate early warnings when something is going wrong in the production process.

The PLF concept is rather new in the European pig industry, but today, early adopters are starting to use it. Some PLF technologies such as pig cough monitors, automatic weighing devices, and camera systems are commercially available now, but the business intelligence software is still under development and under constant improvement. A big European-funded Project (EU-PLF) was started up in 2012 to prove the added value of PLF in 20 commercial farms in Europe. Data collection has been done over 20 fattening periods, and early warning tools for farmers have been developed. Also, automated welfare assessment based on electronic sensor output has been developed.

The output of the sensors (e.g., activity measures with a camera or sound measures with a microphone) is related to animal-based welfare and health indicators such as aggression or respiratory diseases. When sensor signals start to deviate from their expected values, alerts are given to the farmer. In this way the farmer can take an immediate action before the detected change in animal response negatively affects the production performance. These actions range from solving technical problems such as a blocked feeding line, adjusting control settings in the climate and feed controller, or starting a "soft" preventive medical treatment in the animals. In most cases, a preventive medical treatment prevents the further spreading of respiratory diseases in the pen, and the use of antibiotics can be reduced or even precluded.

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Operating principle	Information carrier	Process	Applications	Advantages	Disadvantages
Optical	Shape	Touching	Processing, fingerprinting	Biological characteristics	Contact required
	Shape and color	Image processing	Processing, iris recognition, animal identification	Universal	Complex
	Number code	Code recognition	Automatic identification	Inexpensive	Complicated, dirties easily
	Barcode	Scanner	Trade goods, barcode on new ear markers	Extremely inexpensive markers	Dirties easily
	Electronics with infrared transfer (active)	Transceiver	Service of electrical equipment, animal identification	Large reading range, easily protectable	Only active systems are possible
Electromechanical	Surface acoustic waves (passive)	Transceiver	Goods identification, animal identification	Inexpensive sensor elements, quickly	Only for short information
Electronic	Transponder (active and passive)	Transceiver	Processing, logistics, vehicle security, animal identification	Universally applicable	Relatively expensive

Figure 1. Systems for electronic animal identification (table from Artmann, 1999).

Most of the available PLF behavior sensors are not monitoring the individual pigs, but rather, certain areas in the house. Despite an increasing trend for bigger (100+) groups, most pigs in Europe are kept in a compartment with smaller groups (8–25 pigs per pen). Most sensor output is related to a group of pigs at pen or compartment level. The systems generate more reliable outputs than a human observer because they are available 24 h/d and 7 d/wk .

The most commonly used PLF sensors for pigs are water meters, animal weight sensors, feed supply monitors, camera systems to measure animal activity and distribution, and sound monitoring for respiratory diseases.

In the commercialization of the PLF systems, a stepwise approach is used, starting with feed intake, water intake, and weight. The price of the commercial sensors is no more than a few thousand euros per shed.

Due to the increasing demand for meat, the scale of the farms will grow. Farmers will serve multiple houses (at different locations) and will have less time to care for each individual animal. That means the use of automated monitoring systems presenting up-to-date information to the farm manager will be the only viable option to guarantee the health, welfare, and optimal performance of the animals. Precision farming technologies will provide the license to produce and give an answer to the increasing demand for cheap and healthy food products.

Once the sector starts to understand how valuable the information they produce is, not only to them, but also to other stakeholders such as feeding companies, veterinarians, breeding companies, consultants, processing plants, retailers, and also the consumers, the desire for data will increase exponentially, resulting in a completely different approach to meat production. If we consider what has happened in virtually every other industry over the last 20 yr, this information-based approach becomes inevitable.

Identification of Animals

The identification of individual animals in the pen will enable the livestock managers once again to treat their animals as individuals rather than a herd or flock. The individual care of animals could facilitate the provision of individually tailored diets and environmental control. Both have an enormous effect, and hence, potential on the improvement of productivity and welfare. Individual identification and monitoring of animals is an important step toward enhancing the traceability of livestock products through the supply chain (Naas, 2002). Individual animal identification can technically done by several methods, which are listed in Figure 1.

Water Intake Monitoring

Figure 2. Water meter.

Water consumption monitoring is one of the simplest and most effective tools that a farmer can use to monitor the performance of his animals.

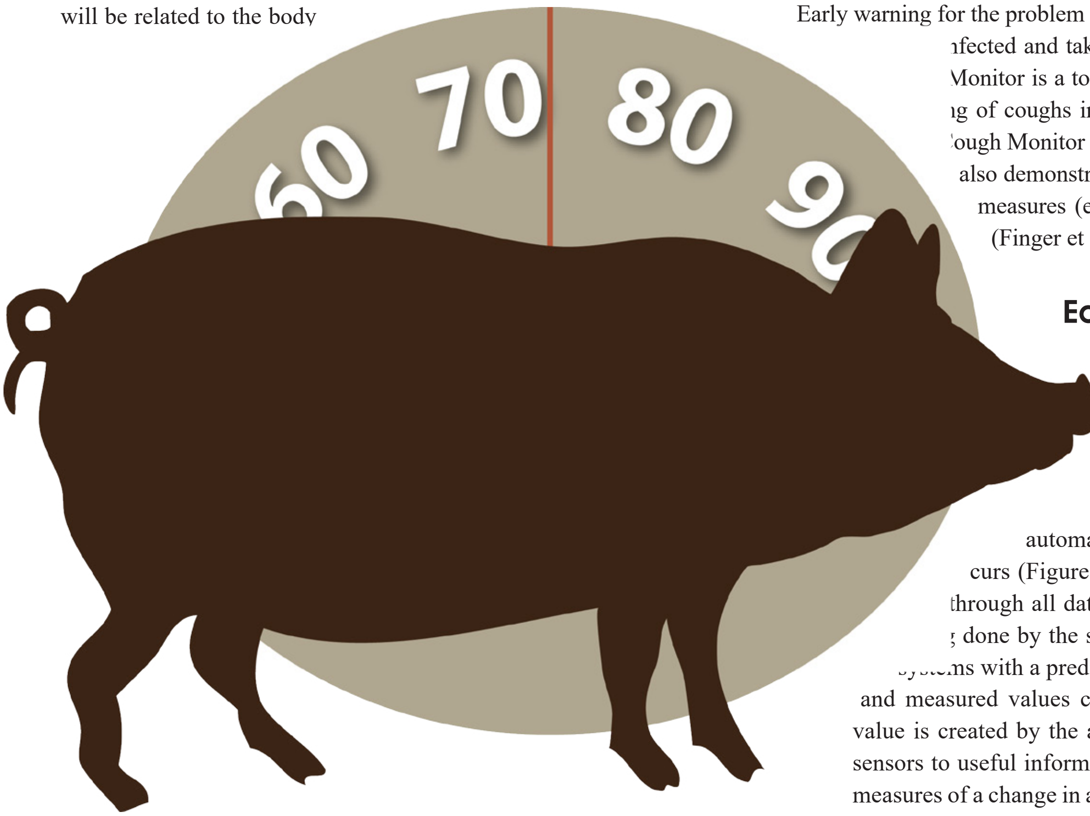
Water meters provide accurate information about water usage of the animals and create the possibility to monitor performance of the animals in a simple and effective way (Figure 2). Water intake can be monitored on shed level, compartment level, pen level, or even individual animal level. Differences between expected and measured water consumption are immediately visible, enabling a response before any abnormalities can affect the welfare or health of the animals. A deviation in the water:feed ration during the day is usually an early sign for health problems (Adriaens et al., 2014).

Moreover, the system warns when crossing the minimum or maximum flow, detecting any blockings or leakages at a very early stage.

Water registration also helps to apply adequate vaccination strategies. Vaccines are usually distributed over drinking water, and therefore, it is important for farmers to know exactly when the water consumption is at the highest level during the day.

Automated Weight Detection

The key in fattening pigs is to optimize the growth performance of the pigs. Therefore, an accurate and non-intrusive method for weighing pigs on a regular basis without the need for labor input is a relevant tool for pig producers. Several research teams attempted to develop a pig weighing system based on image analysis, including scientific teams in the UK (Schofield, 1990; Schofield et al., 1999), Denmark (Brandl and Jorgensen, 1996), the USA (Wang et al., 2008), Belgium (Kashiha et al., 2014a), and Australia (Kollis et al., 2007). The importance of image analysis in the agricultural sector increases day by day, especially within the livestock industries due to the ability of machine vision applications to capture important information related to the competitiveness of the farm, such as the health, growth efficiency, weight, and carcass composition of animals (Banhazi and Black, 2009; Doeschl-Wilson et al., 2005; Whittemore and Schofield, 2000). More recently, several commercial systems (Weight-Detect by PLF-Agritech, eYeScan by Fancom BV, Pigwei by Ymaging, OptiScan, GroStat, and WUGGL) have been introduced. The principle of the automated weight detection by video image analyses is, in theory, quite simple, but in practice, more challenging. First, the pig body needs to be segmented from the pen background. Second, pig body characteristics are determined on the segmented pig body, and they are used to calculate pig-related features such as body area, body length, and width etc. In the last step, these features will be related to the body



weight of the animal by a mathematical model such as a linear regression model. Current commercial systems achieve an accuracy of less than 1.5 kg.

Figure 3 shows the output of the eYeScan system, which obtains the pig's weight using 3D video image recognition. The system includes a hardware module with special image processing software to which a maximum of four cameras can be connected. The analysis software delivered with the system enables continuous growth monitoring of a group of animals.

Monitoring Pig Behavior with eYeNamic

eYeNamic is a system that is used both in pig and poultry farms (Figure 4). The camera-based system is positioned in top-down perspective and generates a visualization of the floor area. The analysis software translates the acquired images into indexes of distribution and activity. These indexes are a measure of the animal's position and movement, and thus, of animal behavior. Image processing technology and mathematical modeling lead to more frequent monitoring of health- and welfare-related responses of livestock animals (Kashiha et al., 2013).

Changes in activity can be caused by abnormal behavior due to aggression (Viazzi et al., 2014), lameness, or other locomotion problems (Kashiha et al., 2014b; Peña Fernández et al., 2016).

Pig Cough Monitoring

Respiratory problems are very common in pig herds, causing significant economic losses. Early treatment of problems is crucial for reducing the economic losses and the amount of antibiotics used in the process. Early warning for the problem allows earlier treatment, causing fewer animals infected and taking less time to cure the animals. The Pig Cough Monitor is a tool for the automated and continuous monitoring of coughs in a pig herd (compartment level). The Pig Cough Monitor can be used as an early warning tool, and it also demonstrates the effects of treatment and preventive measures (e.g., difference between different vaccines) (Finger et al., 2014; Genzow et al., 2014).

Early Warnings with Precision Livestock Farming Systems

The development of early-warning software allows the automated analysis of PLF data, which will lead the farmer automatically toward the problem when it occurs (Figure 5). The farmer will not have to scavenge through all data to perform an analysis because it is being done by the software. By analyzing the data from PLF systems with a predictive model, deviations between expected and measured values can be automatically detected. The added value is created by the algorithms that translate the output of the sensors to useful information to the farmer. It was proven that the measures of a change in animal behavior (monitored with a camera) or respiratory disease (measured with a microphone) are relevant performance indicators. The changes mainly occur as results of technical failures in feed, water or environmental control, animal sickness, or after inappropriate management decisions, such as sudden changes in light schemes.

The alerts created by changes in animal behavior can be reported in dashboards on PC or mobile devices. Farmers are directly guided to the location of the problem, thus saving time and avoiding production losses. As most farmers today can only achieve about 70% of the genetic potential of their flocks, we think that the early warning functionality can result in a 10% higher performance. This will allow a management by exception protocol for the farmer. This procedure has been scientifically described and published (Kashiha et al., 2013).

An example of the early-warning protocol is presented in Figure 6 for the variable water intake of pigs. The early-warning protocol predicts the expected water intake based on historical data. When the measured data lie outside the range of the expected behavior (red color), a warning is raised. This warning can be hard, meaning that a text message or email is sent to the farmer to take immediate action. The warning can also be soft,

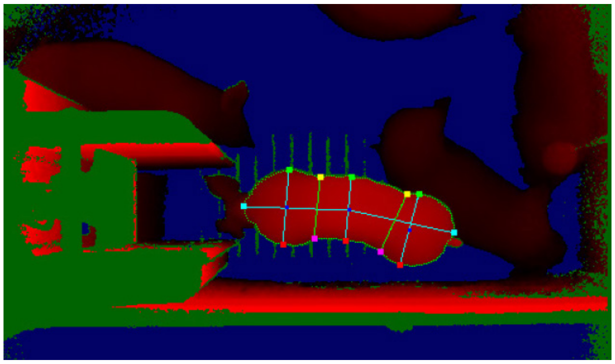


Figure 3. 3D image of eYeScan showing the step in the process where the body characteristics are determined to calculate the pig features such as body width, length, and area.

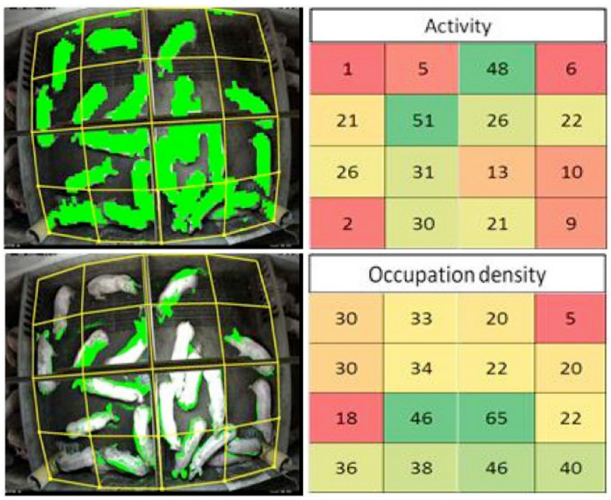


Figure 4. Camera-based system to monitor activity levels and occupation density levels in the pig pen (eYeNamic, Fancom BV, Panningen, Netherlands).

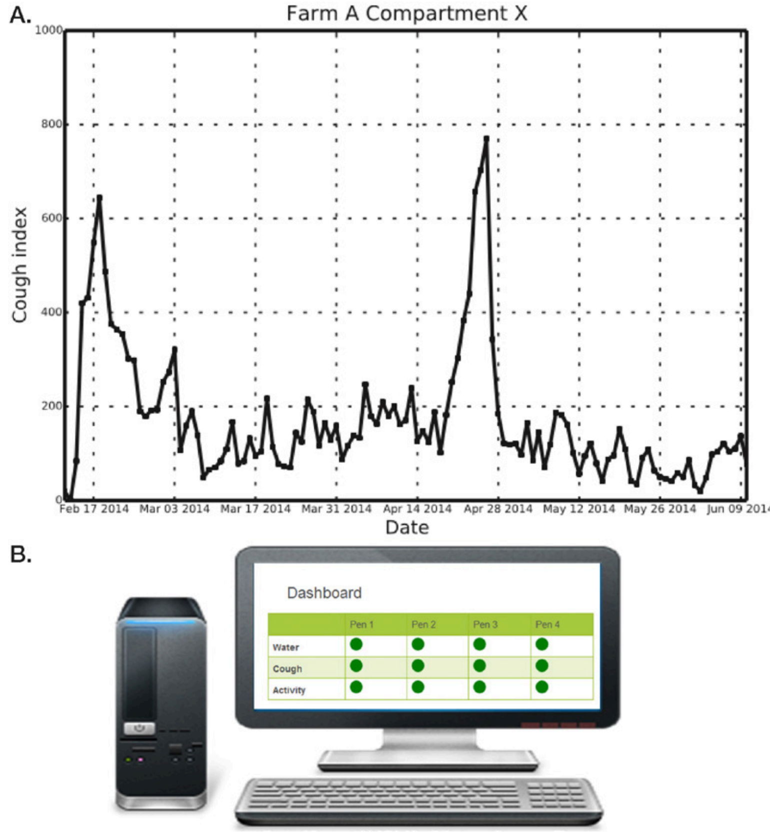


Figure 5. (A) Number of pig coughs detected over a fattening batch. A clear respiratory problem occurs around 19 Apr. 2014. (B) Visualization of a dashboard with early warnings for PLF data. Abnormal deviations in the data will be highlighted and guide the farmer toward the problem area.

Figure 6. Early warning protocol applied to the 24-h water intake of pigs. The early warning protocol predicts the expected behavior of the data based on historical data. Measured data that lies out of the expected range is colored red.

meaning that a notification will made of this alarm in a notification list. Farmers can access this list when they want, preferably once a day to address all alarm situations on their farms. The type of action will depend on the type of warning and on the variable that is causing the alarm.

A similar early-warning protocol was developed for the pig cough monitor to generate early warnings of respiratory diseases to the farmer. The underlying early warning algorithm is however different, and is generated by applying the principles of statistical process control (SPC) on the pig cough data (Oakland, 2003). The procedure to generate the alarms was based on comparing the actual cough data points with control limits based on the running mean and corresponding standard deviations. Alerts were then generated in function of the data points crossing the control limit lines for sufficiently high levels of pig coughing (Berckmans et al., 2015). This procedure is scientifically described in the publication of Hemeryck et al. (unpublished) that has been submitted for publication in *Computers and Electronics in Agriculture.*

Automated Welfare Assessment

There is a growing interest in the automated monitoring of pig welfare. Animal welfare is multifactorial and is, therefore, hard to measure. The European research project Welfare Quality has developed a welfare quality assessment protocol. This protocol is, as many animal welfare projects, based on the Five Freedoms defined by the Brambell Commission (1965)

- · Freedom from hunger and thirst

- · Freedom from discomfort
- · Freedom from pain, injury, or disease

Welfare Principle	Welfare Criteria
Good Feeding	Absence of prolonged hunger
	Absence of prolonged thirst
Good Housing	Comfort around resting
	Thermal comfort
	Ease of movement
Good Health	Absence of injuries
	Absence of disease
	Absence of pain induced by management procedures
Appropriate Behavior	Expression of social behaviors
	Expression of other behaviors
	Good human-animal relationship
	Positive emotional state

- · Freedom to express normal behavior
- · Freedom from fear and distress

The welfare criteria and principles used by the Welfare Quality assessment protocol are:

This welfare assessment is performed by a trained expert. After a visit to a farm (approximately 3 h per shed), this expert is capable of calculating an objective welfare score per welfare principle for that particular farm. This is a time-consuming and complicated process and, moreover, a snapshot of the animals welfare state.

Precision livestock farming offers possibilities to automate the welfare assessment. Many PLF sensors already exist today to automate the assessment of several welfare criteria, such hunger, thirst, and thermal comfort. Other welfare criteria can be deduced indirectly from the automated PLF measurements. Camera and sound systems make it possible to assess bird behavior objectively, so research is now focusing on the objective assessment of welfare criteria based on PLF measures. The ultimate goal should be the development of a dashboard based on the welfare principles and welfare criteria of the welfare quality assessment protocol shown in Figure 7. In this way, animal welfare is objectively assessed 24/7 and without the need of an expert.

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Finishers Welfare Dashboard

Farm: Pig Farmer
Compartment number: 2
Number of pigs at startup: 144
Starting date: 11-12-2011
Current date: 22-12-2011
Day number: 11

Based on Welfare® Quality Science and society improving animal welfare

Welfare paramater	*Indicator*	*score 0 - 1*
Absence of prolonged hunger	Feed intake	0,8
	Feed availability	1,0
Absense of prolonged thirst	Water intake	0,6
	Water availability	1,0
Comfort around resting	Maximal occupation density	1,0
Thermal comfort	Temperature within comfort zone	0,9
	CO2 concentration within comfort zone	1,0
Ease of movement	Average activity index (eYeNamic)	0,6
	Average occupation density (eYeNamic)	0,6
	Space allowance (kg/m2)	0,8
Absence of diseases	Mortality	0,7
	Number of coughs	0,0
	Average welfare score	**0,8**

Figure 7. Example of an automated welfare assessment for fattening pigs based on automated real-time measurements in the house.

Literature Cited

Adriaens, I., J. Maselyne, T. Huybrechts, B. De Ketelaere, S. Millet, J. Vangeyte, A. Van Nuffel, and W. Saeys. 2014. Detecting health problems of individual pigs based on their drinking behaviour. In: Book of Abstracts of the 65th Annual Meeting of the European Federation of Animal Science, EAAP, Copenhagen, Denmark, 25-29 Aug. 2014. Wageningen Academic Publishers.

Artmann, R. 1999. Electronic identification systems: State of the art and their further development. Comput. Electron. Agric. 24:5–26. doi:10.1016/S0168-1699(99)00034-4

Banhazi, T.M., and J.L. Black. 2009. Precision livestock farming: A suite of electronic systems to ensure the application of best practice management on livestock farms. Aust. J. Multi-Discip. Eng. 7(1):1–14.

Berckmans, D., M. Hemeryck, D. Berckmans, E. Vranken, and T. van Waterschoot. 2015. Animal sound… talks! Real-time sound analysis for health monitoring in livestock. In: Proceedings of the International Symposium on Animal Environment & Welfare, Chongqing, China, 23–26 Oct. 2015.

Brambell, R. 1965. Report of the technical committee to enquire into the welfare of animals kept under intensive livestock husbandry systems, Cmd. Great Britain, Parliament, H.M. Stationery Office.

Brandl, N., and E. Jorgensen. 1996. Determination of live weight of pigs from dimensions measured using image analysis. Comput. Electron. Agric. 15(1):57–72. doi:10.1016/0168-1699(96)00003-8

Doeschl-Wilson, A.B., D.M. Green, A.V. Fisher, S.M. Carroll, C.P. Schofield, and C.T. Whittemore. 2005. The relationship between body dimensions of living pigs and their carcass composition. Meat Sci. 70(2):229–240. doi:10.1016/j.meatsci.2005.01.010

Finger, G., M. Hemeryck, C.O. Duran, and M. Genzow. 2014. Practical application of the Pig Cough Monitor in a German fattening pig herd with PRDC. In: Proceedings of the 23rd IPVS Congress, Cancun, Mexico. p. 207– 208.

Genzow, M., C.O. Duran, K. Strutzberg-Minder, G. Finger, and M. Hemeryck. 2014. Monitoring of a commercial fattening herd by means of the Pig Cough Monitor and oral fluid diagnostics. In: Proceedings of the 23rd IPVS Congress, Cancun, Mexico. p. 205– 206.

Kashiha, M., A. Pluk, C. Bahr, E. Vranken, and D. Berckmans. 2013. Development of an early warning system for a broiler house using computer vision. Biosyst. Eng. 116(1):36–45. doi:10.1016/j.biosystemseng.2013.06.004

Kashiha, M., C. Bahr, S. Ott, C. Moons, T. Niewold, F. Ödberg, and D. Berckmans. 2014a. Automatic weight estimation of individual pigs using image analysis. Comput. Electron. Agric. 107:38–44. doi:10.1016/j.compag.2014.06.003

Kashiha, M., C. Bahr, S. Ott, C. Moons, T. Niewold, F. Tuyttens, and D. Berckmans. 2014b. Automatic monitoring of pig locomotion using image analysis. Livest. Sci. 159:141–148. doi:10.1016/j.livsci.2013.11.007

Kollis, K., C.S. Phang, T.M. Banhazi, and S.J. Searle. 2007. Weight estimation using image analysis and statistical modelling: A preliminary study. Appl. Eng. Agric. 23(1):91–96. doi:10.13031/2013.22332

Naas, I.A. 2002. Application of mechatronics to animal production. Agric. Eng. Int.: The CIGR Journal of Scientific Research and Development. 4(2002).

Oakland, J.S. 2003. Statistical process control. 5th ed. Butterworth-Heinemann.

Peña Fernández, A., T. Norton, V. Exadaktylos, E. Vranken, and D. Berckmans. 2016. Analysis of behavioural patterns in broilers using camera-based technology. International Conference in Agricultural Engineering CIGR AgEng 2016. Aarhus, Denmark, 26–29 June 2016.

Schofield, C.P. 1990. Evaluation of image analysis as a means of estimating the weight of pigs. J. Agric. Eng. Res. 47(4):287–296. doi:10.1016/0021-8634(90)80048-Y

Schofield, C.P., J.A. Marchant, R.P. White, N. Brandl, and M. Wilson. 1999. Monitoring pig growth using a prototype imaging system. J. Agric. Eng. Res. 72:205–210. doi:10.1006/jaer.1998.0365

Viazzi, S., G. Ismayilova, M. Oczak, L. Sonoda, M. Fels, M. Guraino, E. Vranken, J. Hartung, C. Bahr, and D. Berckmans. 2014. Image feature extraction for classification of aggressive interactions among pigs. Comput. Electron. Agric. 104:57–62. doi:10.1016/j.compag.2014.03.010

Wang, Y., W. Yang, P. Winter, and L. Walker. 2008. Walk-through weighing of pigs using machine vision and an artificial neural network. Biosyst. Eng. 100:117–125. doi:10.1016/j.biosystemseng.2007.08.008

Whittemore, C.T., and C.P. Schofield. 2000. A case for size and shape scaling for understanding nutrient use in breeding sows and growing pigs. Livest. Prod. Sci. 65(3):203–208. doi:10.1016/S0301-6226(99)00136-0

Source: Temple Grandin